To tap or not to tap: a model-based quantification of the priority placed on smartphone actions

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Significance statement

The extraordinary increase in smartphone usage raises some fundamental questions on human behavior. For instance, what drives people to use the phone or how important is the phone to each individual? In this study we developed a theory to quantify the importance of smartphone interactions based only on smartphone screentouches. Our analysis unravels behavioral processes that are typically shared across the population and perhaps unsurprisingly, 3 of the 4 individuals preferred the phone over doing something else. Theoretically and systematically understanding smartphone behavior could shed light on the behavioral processes underlying spontaneous activities in general.

Abstract

Modern humans are frequently faced with the problem of choosing between using the phone or doing something else. In the laboratory, how people choose between two simple activities is well studied but they cannot address how people solve the ubiquitous problem of using the phone in the real world. Here we extended an existing priority-based decision framework to theoretically link the timing of the touchscreen taps to the priority attributed to the corresponding behaviour. The inter-event times of the output from this decision process could be fully described by a 3 parameter model. Next, we recorded the touchscreen interactions from 84 volunteers for a month-long period and the inter-event times were well described by using the 3 parameter model. Based on the fitted parameters we find that in 76 % of the users the overall (mean) priority of smartphone use is higher than any other activity. The underlying priority distributions estimated from the recordings were typically (82 % of the population) u-shaped with the priority values concentrated at the extreme values. We conclude that the priority attributed to the smartphone is not fixed and the perceived importance of the smartphone transitions from one extreme to another.

Introduction

How decisions are made in the favour of one activity vs. another is a classic problem that cuts across several disciplines Tolman (1938); Thompson and Wankel (1980); Smith and Ratcliff (2004). In empirical and computational neurosciences, addressing this is typically reduced to a choice between two actions to quickly accomplish a task within a time period of a few seconds Smith and Ratcliff (2004). The consequences of operating such decision processes on the overall behavioural organization spanning multiple time scales is not clear. Moreover, the decision processes are conceptualised in the presence of the intermittently available sensory cues or resources and it is not clear how the processes operate when an activity option is continuously present. In particular, smartphones are carried by the users at all the times so how do they decide between using the phone vs. doing something else?

A new class of decision processes is proposed in computational social sciences to explain the response times in emails and surface mails Barabasi (2005); Vázquez et al. (2006); Oliveira and Barabási (2005). In this class, behaviour is organized according to a task list and at each decision point the task for execution is chosen to reflect the perceived priority instead of using either a random or a first-in-first-out selection. This apparently simple process can organize behaviour across time scales resulting in a heavy-tailed distribution of response times and the resulting distributions match what is observed in the timing of emails and surface mails Barabasi (2005); Oliveira and Barabási (2005). That is, the theory explains as to why some messages are immediately responded to by the user while other messages may take several months or even years to respond to. Follow-up studies have extended this framework to predict heavy-tailed inter-event times in person-to-person interactions Oliveira and Vazquez (2009). Nevertheless, smartphones are used for a range of activities that go well beyond person-to-person interactions Smith (2015). There is also a subtle limitation in the existing framework in the sense that it does not allow an assessment of the underlying priority distribution from which the priority is actually drawn at each decision point. In sum, the priority-based decision framework links perceived priority to the timing of the corresponding actions, but the framework in its current form is not designed to extract the priority of smartphone actions vs. other actions.

The continuous availability of the smartphone for activity, the range of activities and the relatively low barrier from intention to execution warrant a focused exploration of the decisions underlying phone use. Although the decision process underlying its use is unclear, there are indirect indicators suggesting that smartphones have a high importance in human behaviour. Firstly, according to market statistics, there were 1.9 billion phone users world-wide in 2015 [1]. Secondly, questionnaires on digital behaviour show that 64% of the American population own smartphones and 46 % of the owners cannot live without it Smith (2015). Finally, separation from the phone can result in measurable distress Clayton et al. (2015).

The goal of this study is to directly extract from the timings of the screen touches the priority placed over smartphone actions vs. other actions. Towards this, we formulated a model that generated smartphone touchscreen touches which heavily depends on the distribution of priorities set to smartphone tasks. We fitted the real inter-touch intervals obtained from 84 volunteers to the modelled parameters to directly and objectively measure the priority placed over touchscreen actions vs. other actions.

Results

Model description

In this model, an individual can perform only two categories of tasks: either a task related to a smartphone screen *touch* or *other* task such as driving a car (see Fig. 1a-b). Every task is associated with a priority level which is a number between 0 and 1. Let $x \in [0, 1]$ denote the priority associated with the *touch* task. In this model we assume that the touchscreen priority distribution $p(x)$ is given by a Beta distribution:

$$p(x) = \mathrm{Beta}(x; a, b) = \frac{x^{a-1}(1-x)^{b-1}}{\mathrm{Beta}(a, b)} \tag{1}$$

where $\mathrm{Beta}(a, b) = \int_0^1 x^{a-1}(1-x)^{b-1}dx$ is the Beta function and acts as a normalisation constant. So if $a > b$, then the *touch* priority distribution is pushed towards higher priorities whereas if $a < b$, lower priorities are favored (see Fig. 1a). Similarly, let $y \in [0, 1]$ denote the priority associated with the *other* task. Since we are interested in the relative priority of the *touch* tasks compared to the *other* tasks we will simply assume that the distribution of priorities for *other* tasks is a

1. https://www.emarketer.com/Article/2-Billion-Consumers-Worldwide-Smartphones-by-2016/1011694

uniform distribution: $q(y) = 1$, see Fig. 1b. The *touch priority index* $\bar{x}$ is defined as the mean of the distribution of priorities for *touch* tasks, i.e. $\bar{x} = \frac{a}{a+b}$. Since the mean of *other* priorities $\bar{y} = \langle y \rangle_{q(y)} = 0.5$, we can state that the *touch* events have in general a higher priority than *other* events if $\bar{x} > 0.5$ and therefore if $a > b$.

Let E_t denote the presence ($E_t = 1$) or the absence ($E_t = 0$) of a *touch* event at time step t (time steps are assumed to be of fixed duration δt). The probability of generating such a *touch* event at time t is a function of both the priority x_t of the *touch* task and the priority y_t of the *other* task (see Fig. 1c):

$$p(E_t = 1 | x_t, y_t) = f(x_t, y_t) \tag{2}$$

For the sake of simplicity, we will assume that $f(x, y) = p$ if $x > y$ where p is called the *permission probability* and $f(x, y) = 0$ otherwise. Permission occurs with probability p and captures several aspects: the inability to use the smart phone because its battery is down or because the individual is in a meeting and cannot use his mobile phone. After the touch event, a new priority x_{t+1} is drawn from $p(x)$. If any of the two above conditions are not satisfied, then the *other* task is chosen and therefore no *touch* event is generated. In this case a new priority y_{t+1} is drawn from $q(y)$ and the procedure starts again. This detailed model is expressed in Table 1a. A sample trace of the evolution of x and y giving a sequence of touches is represented on Fig. 1c.

In order to prevent from drawing a prohibitively large number of times the random variable y, we propose a coarse grain implementation of the touching model which dramatically speeds up simulation time. This coarse grain implementation follows the same approach than the one proposed in Oliveira and Vazquez (2009) and is described in Table 1b and in the Methods. This implementation takes advantage of the fact that we can analytically compute the probability of those long intervals given the priority x of the *touch* task right after the last *touch* (see Methods). As expected, the coarse-grain implementation of the touching model gives identical inter-touch interval (ITI) distribution to the detailed implementation (see Fig. 1d).

Properties of the model

The ITI distribution can be estimated analytically

All together, the touching model described above contains 3 parameters (a, b and p). Because of its latent variable structure (x_t and y_t are the latent variables at time step t and take any real value in the interval $[0, 1]$) and because of the length of the data stream (one month of data corresponds to $5 \cdot 10^7$ time steps of 50ms), fitting such a model is computationally prohibitive with classical methods such as the particle smoother methods Godsill et al. (2004); Kantas et al. (2015). In order to avoid the computational expensive calculations of expectations over the hidden states required in those methods, we directly calculated analytically the marginal distribution over the visible variable $E_{1:T}$. More precisely, we can show that when the permission probability is small, then the inter-touch interval distribution[2] $p(\tau)$ given that $\tau > 1$ can be calculated analytically as

$$p(\tau) \simeq \int_0^1 px(1 - px)^{\tau-2} \text{Beta}(x; a, b) dx \tag{3}$$

It is remarkable that the numerical simulations of the touching model is well captured by the analytical expression of Eq. (3), even up to permission probability of $p = 0.5$ (see Fig. 1d-f). This analytical expression is very convenient for two reasons. First, it massively speeds up the parameter learning and second it allows to directly study the effect of each parameter, which is further explained in the next sub-sections.

2. For notational convenience, we write $p(\tau)$ instead of $p(\tau | \tau > 1)$

The parameter a directly tunes the power-law exponent of the ITI distribution

For large τ, it can be shown (see Methods) that the ITI distribution follows a power-law distribution given by

$$p(\tau) \propto \tau^{-(a+1)} \qquad \tau \gg \tau_{\min} \tag{4}$$

where the power-law exponent is given by $a + 1$, see Fig. 1e and $\tau_{\min}$ defines the onset of the power-law distribution (see also next sub-section). The intuitive reason why this model produces heavy tails in the ITI distribution is that when a priority x is small, the random variable y needs to be drawn on average a very large number of times until it falls below x. This produces very long ITI.

The fact that the power-law exponent directly depends on the parameter a implies that the proportion of very long intervals will decrease if a increases (see Fig. 1e). This makes intuitive sense since a large a corresponds to a *touch* priority distribution pushed towards higher priorities (see Fig. 1a) which implies that *touch* tasks are more often executed and therefore this gives less long intervals.

The permission probability p scales the onset of the power-law distribution

The permission probability p fulfills several roles in this touching model. First, as mentioned in the model definition above, it reflects the fact that subject don't necessarily chose the action with the highest probability. If the priority of the *touch* task is higher than the *other* task, then the *touch* task is chosen with probability p.

Secondly, setting this parameter p such that $p < 1$ removes a singularity in the model. Indeed, in the limit of $p \to 1$, most of the inter-touch intervals are concentrated at the value of $\tau = 1$. The reason is the following. Let us assume that there is an event at time $t = 0$ where we have $x_0 > y_0$. If the next priority for the touchscreen task x_1 is larger than y_0, then there is a next event at $t = 1$ and the priority for the other task remains the same, i.e. $y_1 = y_0$. If, on the contrary $x_1 < y_0$, then at the time of the next event at time $t = \tau$, the priority for the other task y_τ will be smaller than the touchscreen task $x_\tau = x_1$ which is smaller than y_0. Therefore the value of y (at the time of an event) either stays the same or decreases. When it approaches zero, it becomes impossible for the priority x to fall below y and therefore there are events every time steps. By assuming that $p < 1$, the permission to touch the screen can be denied and therefore allow a potential increase in y at the time of the next event. The consequence of this $p < 1$ assumption is that the inter-event distribution is not anymore concentrated at $\tau = 1$.

Finally, the parameter p tunes the onset of the power-law distribution (see Fig. 1d). More precisely, the permission probability scales inversely with $\tau_{\min}$, see Eq. (15). This can be understood intuitively since for low permission probability, and for small ITI, the touch generation process is similar to a Poisson process where the touching rate scales with $1/p$ thereby defining a typical scale.

The parameter b tunes the kink of the ITI distribution

Finally, the parameter b also scales the onset of the power-law distribution (see Eq. (15) and Fig. 1f). If b increases, it increases $\tau_{\min}$ whereas if b falls below one, it can produce ITI with a non-monotonic derivative of $\log p(\tau)$ (see Fig. 1f, for $b = 0.2$). This feature will help better fit experimental ITI distribution which display such a slight kink (see Fig. 2a,b).

The priority distribution can be inferred from list of ITIs

In order to fit the model to the data, we computed the log-likelihood of the set of inter-touch intervals $\mathcal{D} = \{\tau_i\}_{i=1}^N$ given the parameters $\theta = (a, b, p)$:

$$L = p(\mathcal{D}|\theta) = \sum_{i=1}^{N} \log p(\tau_i) \tag{5}$$

where the ITI distribution $p(\tau_i)$ is taken from Eq. (3) and τ_i denotes the number of bins of $\delta t = 50$ ms (i.e. the i^{th} interval is given by $\tau_i \delta t$). By maximising the log-likelihood, we found that the ITI distribution for each subject can be well captured by the model (see the fit for one subject in Fig. 2a). So, from the fitted parameters a and b, we obtain the *touch* priority distribution $p(x)$ (see Eq. (1) and Fig. 2a inset). In particular, found that for this subject, the smartphone tasks are mostly attributed high priority, sometimes very low priorities and very few times medium priority.

So, the relevance of the model is twofold. First, since the model can fit well ITI, it can be used to describe the data in a compressed way. It reduces weeks of data into 3 parameters. Secondly, it allows to determine the priority distribution $p(x)$ from the empirical inter-touch interval distribution.

In order to determine whether this 3 parameter model would overfit, we conducted a model comparison. In particular, for each subject, we computed the Bayesian Information Criterion (BIC) for the 3 parameter model (BIC(3)) as well as for a 2 parameter version of the model (BIC(2)) where $b = 1$ (see Fig. S1). We found that for 78 (out of the 84) subjects, the 3 parameter model could not be rejected $\Delta BIC = BIC(3) - BIC(2) < 0$. 5 out of the 6 remaining subjects have a fitted value of b (in the 3 parameter model) anyway close to 1 (i.e. in the interval $[0.91, 1.03]$).

Population results

By repeating the fitting procedure described above for each subject, we extracted the model parameters for each subject (see Fig. 2b). The distribution of the permission probability p over the different subjects (see Fig. 2c) concentrated around small values of p (median(p) = 0.14) which is convenient for the proposed fitting procedure which is only valid for small p [3].

By learning the touch priority parameters a and b for each subject (see Fig. 2d), we can calculate the priority index $\bar{x} = a/(a+b)$ which corresponds to the the mean of the touch priority distribution (see Fig. 2d). We found that for 76% of the subjects (see Fig. 2c), the mean of their touch priority distribution is larger than the mean of the *other* distribution - a condition which is fulfilled when $a > b$ (see the red shaded area in Fig. 2d). In other words, for those subjects touching the smartphone is more important than doing something else.

From the priority distribution, we can also calculate the spread σ of the distribution. For a Beta distribution, the s.t.d is given by $\sigma = \sqrt{ab}/((a+b)\sqrt{a+b+1})$. We found that 84 % of the subjects have a touch priority spread which is bigger than $\sigma^* = 1/(2\sqrt{3}) \simeq 0.29$ which corresponds to the s.t.d of a uniform distribution. So the inferred priority distribution is typically U-shaped (see Fig. 2b, inset).

Discussion

In this study, we proposed a method to infer the priority distribution of using the smartphone from the corresponding inter-touch interval distribution. We showed that 3 out of 4 subjects prefer to interact with their smartphone rather than perform other tasks. This was consistent with previous reports that pointed to the high perceived importance of smartphones. For instance, according to self reports 64% of teenagers prefer texting on the phone vs. person to person communications [4].

3. For $p \to 1$, the analytical approximation for the ITI distribution - which is used for the fitting procedure - does not hold.
4. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4260009/

Moreover, the touch priority distribution is typically U-shaped in the sample population suggesting that underlying mechanisms driving smartphone use may be shared.

The core idea used to link the inter-touch intervals and the priority was the priority-based decision process. In neuroscience and psychology, decision processes have been proposed that enable a system to choose between one or the other action Smith and Ratcliff (2004); Carpenter (2004). However, these processes are only explored in terms of very limited time-scales (below a minute). In contrast, the originally proposed priority-based decision process proposed by Barabasi (2005) is able to explain the *response times* in surface mail and email correspondences across time scales (above a second). Our work further extended this idea to an *emission process* such that the priority distribution attributed to one type of activity could be inferred based on the corresponding inter-event times.

The decision processes considered in the past to explain the behavioural structure spanning multiple time scales typically focus the attention on ITI larger than a minimal interval $\tau_{\min}$ above which the distribution becomes power-law Malmgren et al. (2008); Oliveira and Barabási (2005); Proekt et al. (2012); Reynolds et al. (2007). It is remarkable here that our touching model captures reasonably well ITI for $\tau < \tau_{\min}$. For $\tau > \tau_{\min}$, it should be noted that unlike other existing priority-based models Oliveira and Vazquez (2009) our model is not restricted to rational power-law exponents. Indeed in our framework the power-law exponent is given by $a + 1$ where a can take any real positive value. In contrast, in the work of Oliveira and Vazquez (2009), the exponent α is determined by the length L [5] of the list of tasks, i.e. $\alpha = 1 + 1/(L - 1)$. In our study, the power-law exponent is 1.71 ± 0.14 which is different from frequently found exponent of 1, 1.5 or 2.

A common aspect shared across the population was the U-shaped priority distribution suggesting that smartphone actions either receive a very high or a very low priority at each decision point. These distinct priorities may reflect the different activities on the phone and/or how the same activities may occupy intense importance at any point of time. Still, the shared U-shaped distribution did not mean that all individuals similarly used their phones. The proportion of the high to low activities varied substantially from person to person.

This study is an important step towards generating a more realistic model of smartphone touching dynamics. Extensions of this model could include physiological limitations on how quickly the phone may be operated as well as fatigue that could accumulate over time in order to better describe the distribution of sub-second ITIs. It is however remarkable to how well can this simple 3 parameter model describe ITI distribution over several magnitudes.

Methods

Subjects

A total of 84 individuals were recruited by using campus wide announcements at the University of Zurich and ETH Zurich. Ownership of a non-shared touchscreen smartphone with an android operating system was a pre-requisite for participation. All experimental procedures were approved according to the Swiss Human Research Act by the cantons of Zurich and Vaud. The procedures also conformed to the Helsinki Declaration. The volunteers provided written and informed consent to participate in the study.

Smartphone data collection

A custom-designed software application (app, Touchometer) that could record the touchscreen events with a maximum error of 5 ms Ghosh and Balerna (2016) was installed on each participant's phone. To determine this accuracy, controlled test touches were done at precisely 150, 300 and 600 ms while

5. Technically, Oliveira and Vazquez (2009) assume that an event occurs only if the interacting task for both agents A and B have the highest priority compared to all other tasks of length L_A (for agent A) and L_B for agent B. For simplicity we denoted $L = L_A = L_B$.

the Touchometer recorded at 147, 301 and 600 ms respectively, with standard deviations less than 15 ms (interquartile range less than 5 ms). The app posed as a service to gather the timestamps of touchscreen events that were generated when the screen was in an unlocked state. The operation was verified in a subset of phones by using visually monitored tactile events. The data was stored locally and transmitted by the user at the end of the study via secure email. One subject was eliminated as the app intermittently crashed after a software update. The smartphone data were processed by using MATLAB (MathWorks, USA).

Coarse-Grain implementation

In order to speed-up simulation time, we used the following implementation of the touching model which we call *coarse-grain implementation.* Let us assume that at time $t = 0$ an event has occurred, i.e. $x_0 > y_0$. At time step $t = 1$ a new priority $x_1 \equiv x$ is drawn from $p(x)$. If $x_1 > y_1$ (where $y_1 = y_0$) and the permission is granted, there is another event at $t = 1$. So the probability of having an interval of $\tau = 1$ depends only on y_0 whereas the probability of having an interval $\tau > 1$ will depend only on $x = x_1$. The idea of this coarse grain model is to calculate explicitly this probability distribution $Q(\tau|x)$ for $\tau > 1$ thereby avoiding to sample a large number of times the random variable y.

Let $\pi(x)$ denote the probability of an event at time $t > 1$ given that the priority for the touch task is x_1 at time $t = 1$ (i.e. $x = x_1$). An event can occur if two conditions are met, i.e. if $y < x$ and if the permission is given (with probability p). Since those two conditions are independent, we can write them as a product:

$$\pi(x) = p \int_0^x q(y)dy = px \tag{6}$$

where the last equality stems from the fact that we assumed that $q(y) = 1$. The distribution $Q(\tau|x)$ of ITI intervals for a given x is given by

$$Q(\tau|x) = \pi(x)(1 - \pi(x))^{\tau-2} \quad \tau > 1 \tag{7}$$

Note that this quantity is well normalized since $\sum_{\tau=2}^{\infty} Q(\tau|x) = 1$. This coarse-grain model is summarized in Table 1b. As we can see on Fig. 1d, the inter-touch interval distribution from the coarse grain model is in perfect agreement with the distribution obtained from the detailed model.

Calculation of the ITI distribution

In the previous section, we saw that the probability of having an interval of $\tau = 1$ depends only on y_0 whereas the probability of having $\tau > 1$ depends on x_1. So, in order to calculate the overall inter-touch interval distribution $p(\tau)$, we need to average over the distribution $p(y_0|E_0 = 1)$ of priority values y_0 at the times of the events ($E_0 = 1$ denotes the fact that there is an event at time $t = 0$) for $\tau = 1$ and average over the distribution $p(x_1|E_0 = 1, E_1 = 0)$ of priority values x_1 given that there is an event at time $t = 0$ ($E_0 = 1$) and no event at time $t = 1$ ($E_1 = 0$) for $\tau > 1$:

$$p(\tau) = \begin{cases} p \int_0^1 p(x_1 > y_0)p(y_0|E_0 = 1)dy_0 & \text{if } \tau = 1 \\ (1 - p(1)) \int_0^1 Q(\tau|x_1)p(x_1|E_0 = 1, E_1 = 0)dx_1 & \text{if } \tau > 1 \end{cases} \tag{8}$$

where the distribution $p(x_1|E_0 = 1, E_1 = 0)$ is given by

$$p(x_1|E_0 = 1, E_1 = 0) = \frac{p(E_1 = 0|x_1, E_0 = 1)}{\int_0^1 p(E_1 = 0|x, E_0 = 1)p(x)dx} p(x_1) \tag{9}$$

In the limit of small p, we have $p(E_1 = 0|x_1, E_0 = 1) \to 1$ and therefore

$$p(x_1|E_0 = 1, E_1 = 0) \simeq p(x_1) \tag{10}$$

For small p and for $\tau > 1$, we have

$$\begin{aligned} p(\tau) &\simeq \int_0^1 Q(\tau|x)p(x)dx \\ &= \int_0^1 px(1-px)^{\tau-2}\mathrm{Beta}(x;a,b)dx \\ &= \frac{p}{\mathrm{Beta}(a,b)}\int_0^1 x^a(1-px)^{\tau-2}(1-x)^{b-1}dx \end{aligned} \tag{11}$$

Calculation of the power-law exponent

For large τ, the factor $(1-px)^{\tau-2}$ approaches[6] 0 for $x > 1/(p(\tau-2))$. This allows to Taylor expand the third factor around 0, i.e. $(1-x)^{b-1} \simeq 1-(b-1)x$ which can be used to split the integral into a sum of 2 simpler integrals:

$$\begin{aligned} p(\tau) &\simeq \frac{p}{\mathrm{Beta}(a,b)}\left(\int_0^1 x^a(1-px)^{\tau-2}dx - (b-1)\int_0^1 x^{a+1}(1-px)^{\tau-2}dx\right) \\ &= \frac{p^{-a}}{\mathrm{Beta}(a,b)}\left(\int_0^p z^a(1-z)^{\tau-2}dz - \frac{b-1}{p}\int_0^p z^{a+1}(1-z)^{\tau-2}dz\right) \end{aligned} \tag{12}$$

where the last equation was obtained by the following change of variable $z = px$. Here again, let $y^* = 1/(\tau-2)$ denote the value of y above which the factor $(1-y)^{\tau-2}$ vanishes. Then if $y^* \ll p$ (which corresponds to $\tau \gg 1/p+2$), then the integration interval can be extended from $[0,p]$ to $[0,1]$ allowing to express the result as a function of Beta functions:

$$\begin{aligned} p(\tau) &\simeq \frac{p^{-a}}{\mathrm{Beta}(a,b)}\left(\mathrm{Beta}(a+1,\tau-1) - \frac{b-1}{p}\mathrm{Beta}(a+2,\tau-1)\right) \\ &\simeq \frac{p^{-a}a\Gamma(a+b)}{\Gamma(b)}\left(\tau^{-(a+1)} - \frac{(b-1)(a+1)}{p}\tau^{-(a+2)}\right) \end{aligned} \tag{13}$$

where we used the fact that the Beta function can be expressed as $\mathrm{Beta}(a,b) = \Gamma(a)\Gamma(b)/\Gamma(a+b)$ and $\Gamma(a) = \int_0^\infty t^{a-1}e^{-t}dt$ is the gamma function. We also used the fact for large z, $\Gamma(z+a)/\Gamma(z) \to z^a$. Since for large τ, the first term in the parenthesis of Eq. (13) will dominate, we have

$$p(\tau) \simeq \frac{p^{-a}a\Gamma(a+b)}{\Gamma(b)}\tau^{-(a+1)}, \qquad \tau \gg \tau_{\min} \tag{14}$$

where the onset of the power-law distribution $\tau_{\min}$ depends on the model parameters and in particular inversely scales with the permission probability:

$$\tau_{\min} \simeq \frac{\max(b-1,1)(a+1)}{p} + 2 \tag{15}$$

This condition is obtained by combining the conditions required to derive Eq. (13) (i.e. $\tau \gg 1/p+2$) and Eq. (14) (i.e. $\tau \gg (b-1)(a+1)/p$).

6. This can be found by Taylor expansion: $(1-px)^{\tau-2} \simeq 1-p(\tau-2)x$. Therefore $1-p(\tau-2)x^* = 0 \Rightarrow x^* = 1/(p(\tau-2))$

Author contribution

AG collected the data and conceived the project with JPP. JPP and AG designed the study, developed the model used here and drafted the manuscript. JPP analyzed the data and formulated the mathematical model, aided by AG.

Conflicts of interest

AG is an inventor of the patent-pending technology used to track touchscreen interactions in this study. AG and JPP are co-founders of QuantActions GmbH, a company focused on quantifying human behaviour through smartphone interactions.

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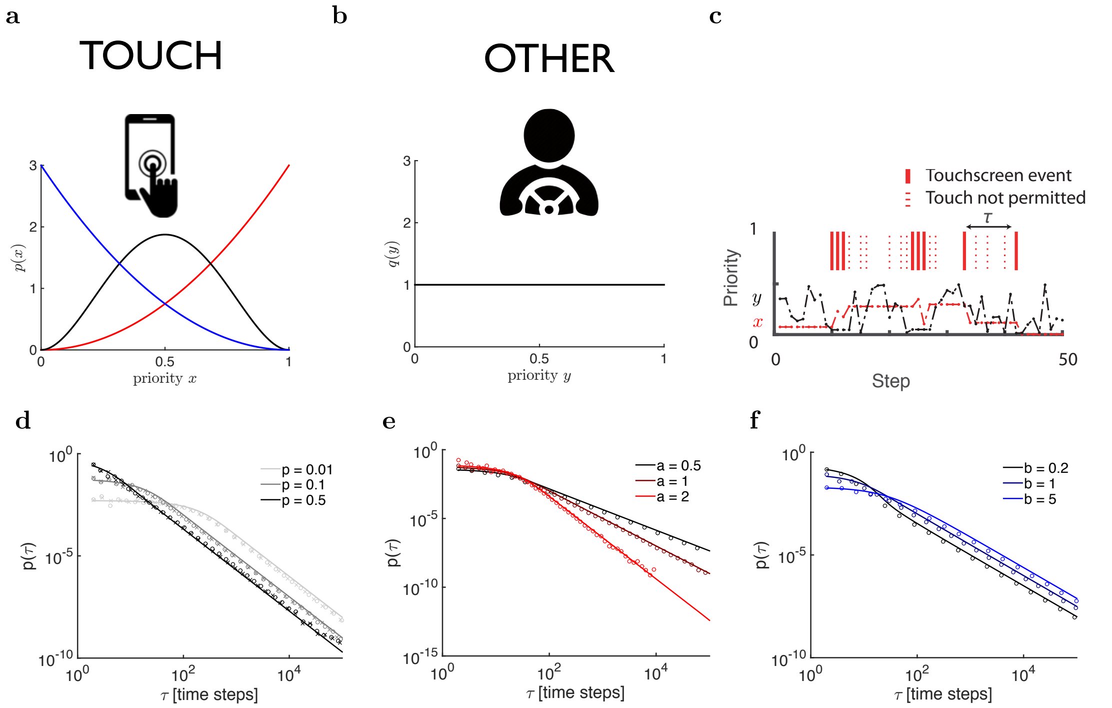

Figure 1: Smartphone Touching Model. **a** Priority distribution for the *touch* tasks for various parameters, see Eq. (1). (red: $a = 3$, $b = 1$, black: $a = b = 3$, $a = 1$, $b = 3$). **b** Priority distribution for the *other* tasks. **c** Sample trace from the priority model. **d-f** Properties of the model. Distribution $p(\tau)$ of inter-touch intervals τ (**d**) for various permission probability p, ($a = 1$, $b = 1$) (**e**) for various a ($p = 0.1$, $b = 1$) and (**f**) for various b, ($p = 0.2$, $a = 0.5$). Analytics (solid lines, see Eq. (3) match well simulations from the coarse grain model (circles) and detailed model (crosses).

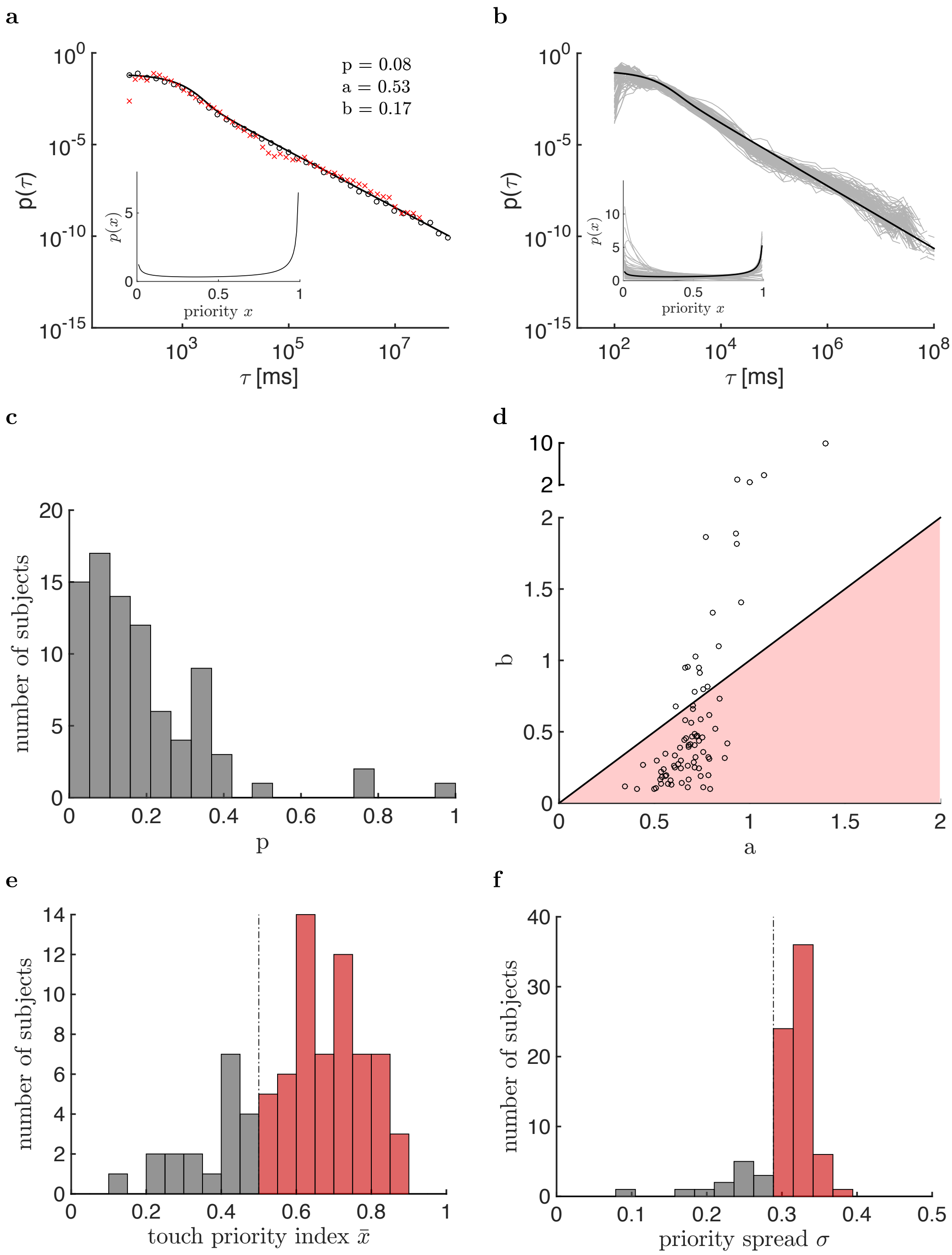

Figure 2: Results. **a** ITI distribution for one given subject (red crosses) is well captured model (solid line: analytics, circle: simulations of the coarse-grain touch model). **Inset** Touch priority distribution inferred for this subject. **b** Same as in **a** but for each of the 84 subjects (gray lines). Solid lines are obtained with the median of the fitted parameters i.e. $a = 0.7$, $b = 0.4$ and $p = 0.14$. **c** Distribution of the permission probability p. **d** Each dot represents the fitted touch priority parameter a and b for one subject. If $a > b$ (red shaded region), the average *touch* priority is higher than the average *other* priority. **e** Distribution of the priority index $\bar{x} = a/(a+b)$. 76% of subjects (red) have a higher touch priority index > 0.5 (i.e. the average touch priority is higher than the average priority of other tasks). **f** Distribution of the spread σ of the touch priority distribution. 84% of subjects (red) have a touch priority spread larger than the s.t.d. corresponding to a uniform distribution.

a Detailed model

Input: p, k, N;
$x \sim p(x)$; $y \sim q(y)$;
$n = 0$, $t = 0$;
while $n < N$ **do**
  $t = t + 1$;
  if $x > y$ and Rand $< p$ **then**
    $n = n + 1$; $Event(n) = t$;
    $x \sim p(x)$;
  else
    $y \sim q(y)$;
  end
end
Return: $Event$;

b Coarse Grain model

Input: p, k, N;
$x \sim p(x)$; $y \sim q(y)$;
$n = 0$, $t = 0$;
while $n < N$ **do**
  n = n+1;
  if $x > y$ and Rand $< p$ **then**
    $t = t + 1$;
  else
    $\tau \sim Q(\tau|x)$ % see Eq. 7 ;
    $t = t + \tau$;
    $y^* \sim q(y)$, $y = xy^*$;
  end
  $Event(n) = t$;
  $x \sim p(x)$;
end
Return: $Event$;

Table 1: **a**. Detailed priority model which generates a list of N event times. **b** Coarse grain model which is much faster to simulate.

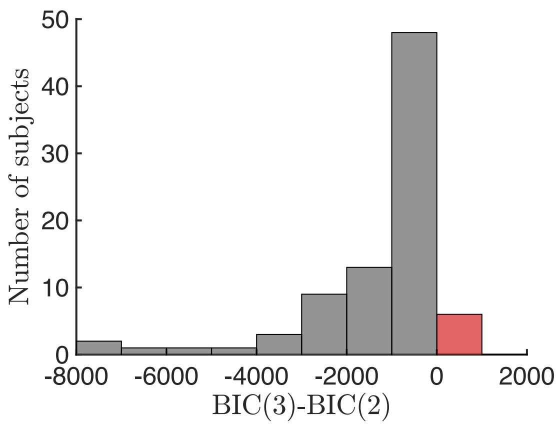

Figure S1: Model comparison. Distribution of the difference between the Bayesian Information Criterion (BIC(3)) of the full touching model - which contains 3 parameters and the BIC(2) for the restricted touching model (where $b = 1$) and therefore contains only 2 free parameters. Only 6 subjects have BIC(3)-BIC(2)> 0 (red shaded) and therefore can be better described by the 2 parameter model instead of the 3 parameter model.